International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 1, January - 2014

A New Morphology Algorithm for Microcalcifications Detection in Fuzzy Mammograms Images

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Abstract

The main concerns of this paper is to illustrate how morphology Mathematics operations are applied in the domain of digital image processing. In the sequel we present and discuss how a new algorithm based on mathematical morphology operators is able to detect well the microcalcifications in mammograms images. We apply some of these operators to build an algorithm applied on digital images. We use the erosion operator by reconstruction with isotropic structuring element, flowed by the Segmentation based by contrast enhancement to find our new powerful algorithm. This algorithm is very efficient to detect well the microcalcifications malignant or benign in mammography images. We use also another algorithm to extract the minima regions from original image. We focus our zoom in this region that we have the more probability to find the microcalcifications. The application of our algorithm on a very fuzzy image leads us to deduce that our method is very powerful to detect well the microcalcification.

Keyword: *Mammogram image, Morphology Matimatics Operator, Fuzzy image, Microcalcifications.*

1. Introduction

Microcalcifications detection in mammograms images is one of the most problems in digital image medical. In mammography we have two types of problem: Microcalcifications and opacities. In the sequel there are two types of microcalcifications, benign or malignant. Then we ask if we can find a powerful method to detect well these microcalcifications.

Currently, a large number of institutions around the world are actively engaged in research on mammograms. Traditionally, the diagnosis of local recurrence has been made with the mammography, ultrasonography, CT scan and magnetic resonance imaging (MRI), the latter two also being used when there is suspicion of distant recurrence, and the bone scintigraphy when there is suspicion of metastatic bone disease or in those cases with high risk of disease [1, 2].

Hence, detection of microcalcifications considered the additional advantages of evaluating the cases of suspicion of breast cancer recurrence with a FDG-PET scan[3, 4] and more recently by the combination of morphological and functional images, such as CT scan and FDG-PET[5, 6].

Mathematical morphology operator is a powerful, shaped-based method often used in image processing. It was invented by Georges Matheron and Jean Serra who worked on the automatic analysis of images occurring in mineralogy and petrography [7, 8, 9, 10]. Meanwhile the method has found immense applications in [11].

However Tasto et al. [12, 13] described an algorithm for detection of microcalcifications on mammograms, which were based on identification of grayscale value in a mammographic image. Note that Brockett and Maragos [14, 15] have independently developed a theory generating multiscale morphological erosion-dilatation of a more general type.

As mentioned in various papers, the morphology mathematics plays a central role in the detection problem of the contours. The objective of this research is to propose a new algorithm, which can be applied to mammograms images, in the aim to detect microcalcifications.

The content of this paper is organized as follows. We start by presenting some morphology mathematics operators. The microcalcifications malignant and benign are presented.

The comparison of the proposed algorithm with other permits us to show the efficiency of our method. We introduce a new method of microcalcifications detection. The comparison of the proposed algorithm with other permits us to show the efficiency of our method.

2. Materials and methods

2.1. The morphology mathematics

The difference of sets A and B denoted A-B, is the set all elements that belong to A but not to B,

$$A-B=\{w/w\in A, w\notin B\}$$

In addition to the preceding basic operations, morphological operations often require two operators that are specific to sets whose elements are pixel coordinates. The reflection of set B, denoted $\hat{B}$, is defined as

$$\hat{B}=\{w/w=-b,\ for b\in B\}$$

The translation of set A by point $z=(z_1,z_2)$, denoted $(A)_z$, is defined as

$$(A)_z=\{c/c=a+z,\ for a\in A\}$$

2.1.1. Dilation and Erosion

The operations of dilation and erosion are fundamental to morphological image processing. Many of the algorithms presented in this search are based on these operations, which are defined and illustrated in the discussion that follows.

Dilation is an operation that "grows" or "thickens" objects in a binary image the specific manner and extent of this thickening is controlled by a shape referred to as a structuring element.

Mathematically, dilation is defined in terms of set operations. The dilation of A by B, denoted $A\oplus B$, is defined as

$$A\oplus B=\left\{z/\left(\hat{B}\right)_z\cap A\neq\varnothing\right\}$$

where $\varnothing$ is the empty set and B is the structuring element. In words, the dilation of A by B is the set consisting of all the structuring element origin locations where the reflected and translated B overlaps at least some portion of A. The translation of the structuring element in dilation is similar to the mechanics of spatial convolution.

Dilation is commutative: that is $A\oplus B=B\oplus A$. It is a convention in image processing to let the first operand of $A\oplus B$ be the image and the second operand be the structuring element, which usually is much smaller than the image.

Erosion "shrinks" or "thins" objects in a binary image. As in dilation, the manner and extent of shrinking is controlled by a structuring element.

The mathematical definition of erosion is similar to that of dilation. The erosion of A by B, denoted $A\Theta B$, is defined as

$$A\Theta B=\left\{z/(B)_z\cap A^c\neq\varnothing\right\}$$

In other words, erosion of A by B the set consisting of all the structuring element origin locations where the reflected and translated B has no overlap with background of A. The translation of the structuring element in dilation is similar to the mechanics of spatial convolution.

In practical image-processing applications, dilation and erosion are used most often in various combinations. An image will undergo a series of dilations and/or erosions using the same, or sometimes different, structuring elements.

2.1.2. Grayscale Morphology filters of dilation and erosion

All the binary morphological operations have natural extensions to gray-scale images. In this paper, as in the binary case, we work with dilation and erosion which for gray-scale images are defined in terms of minima and maxima of pixel neighborhoods.

The gray-scale dilation of *f* by structuring element b, denoted $f\oplus b$, is defined as (1)

$$(f\oplus b)(x,y)=\max\{f(x-x',y-y')+b(x'+y')/(x'+y')\in D_b\}$$

where D_b is the domain of b and *f(x,y)* is assumed to equal outside the domain of *f*.

The gray-scale erosion of *f* by structuring element b, denoted $f\Theta b$, is defined as (2)

$$(f\Theta b)(x,y)=\min\{f(x+x',y+y')-b(x'+y')/(x'+y')\in D_b\}$$

where D_b is the domain of b and *f(x,y)* is assumed to be $+\infty$ outside the domain of *f*.

The formulas (1) and (2) implements a process similar to the concept of spatial convolution, see the more in [16].

2.2 Segmentation: Extracting the region of interest

The aim of the segmentation process is to extract the abnormal regions or regions with high probability of abnormality that is called Regions Of Interest (ROI), see [7, 17], from the digital mammography image. The segmentation of lesion in mammographic images is known to be a difficult step toward automatic breast cancer diagnosis, due to the very low contrast of these images. Many different approaches to the problem of lesion segmentation can be found in the literature [18, 19]. We applied the histogram thresholding (algorithm1), which uses intensity values to split the image domain into segmented objects regions of interest and background areas. We aim to detect abnormal and normal lesions in a mammogram by identifying suspicious regions of tissue, where a suspicious region is an abnormal region or a region with a high probability of abnormality. Here the segmentation process is applied on the original image. The main steps of the threshold segmentation algorithm are provided below.

Algorithm 1 Threshold segmentation algorithm

Input: original mammogram image
Output: Segmented region of interest
1: Get the histogram of image original

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 1, January - 2014

2: Get threshold value T from the histogram
3: Apply threshold segmentation as the following
  i : each pixel in the image
  ii : if value of the pixel in the input image > the threshold value T then
  iii : assign this value to the corresponding pixel in output image
  iv : Else
  v : set the value of corresponding pixel in output image with Zero
  vi : end if
4: The segmented image

2.3 The microcalcifications malignant and benign

Microcalcification clusters are groups of small and brilliant objects of different shape and intensity in a very noisy background. A microcalcification is a rather small in diameter but very brilliant object. Some of them, either grouped in clusters or isolated, may indicate the presence of a tumor [20, 21].

When analyzing calcifications in the absence of a tumor, see [22], or when disregarding the associated tumor, the most important factors are the *distribution* of the calcifications and the *form, size, and density* of the individual particles. The number of the individual calcifications is of little importance when making a diagnosis.

Although the actual number of calcifications has been considered by some to have diagnostic significance, the form, size, and density of the calcifications are of far greater importance. Magnification mammography in particular has demonstrated that the number of calcifications detected can be highly dependent upon the mammography technique. The granular- type calcifications are often innumerable, as one can understand from the pathological background. It is important to note that the casting type calcifications are so characteristic of Grade 2-Grade 3, poorly differentiated carcinoma in situ that the diagnosis can be made on the basis of one or two such calcifications alone.

The benign calcifications within lobules may be numerous and scattered throughout much of the parenchyma. The distribution of plasma cell mastitis is generally bilateral and evenly scattered, with the calcifications following the course of the ducts. The cluster or multiple cluster *distribution* of the calcifications indicates that they are localized with the lobules. Differentiation among the benign pathological entities leading to calcification within the lobules (fibrocystic change, sclerosing adenosis, blunt duct adenosis) is the task of the pathologist.

3. Proposed algorithm

We propose a new algorithm based of morphology mathematics operator for detecting microcalcifications in mammograms images. These microcalcifications are brilliant in the complement image, so the first time we apply the erosion operator of original image and we find eroded image followed by the complement of this image. We apply also the contrast enhancement on eroded image and we find output image. In the second step we apply the algorithm1presented in section2 to extract the Region Of Interest (ROI). This technic helps us to focus our work on this region and his correspondence region on the output image. We present our algorithm as follows,

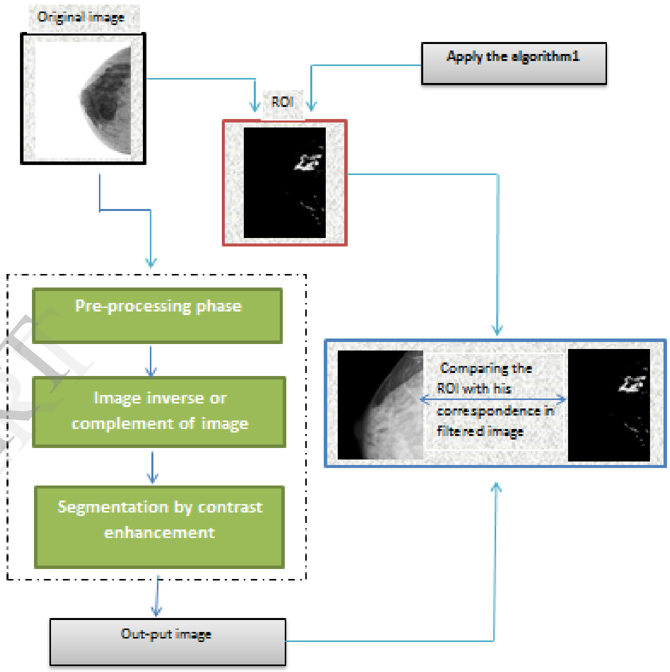
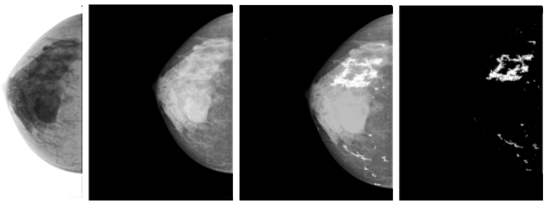


Figure 1. Detecting microcalcifications by proposed algorithm.

4. Results

The first time we apply the algorithm1 and we obtain an image that emphasizes the deepest minima and removes all others (Figure 2), we create then a marker image that pinpoints the minima of interest. This marker image is created by explicitly setting certain pixels to specific values to extract the features by algorithm 1. We create new minima in the original image by the marker image. This marker changes the values of all the other pixels in the image to eliminate the other minima.

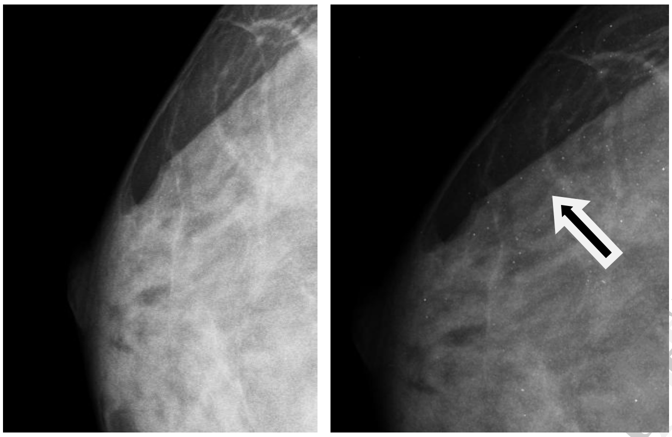
The figure2 shows the original image, the complement of this image, the image without the ROI and the locations of the deepest minima of original image called maker image.



(i) (ii) (iii) (iv)

Figure 2. (i) Shows the original image, (ii) shows the image complement, (iii) shows the image without the ROI, (iv) shows the extracted ROI.

The Figure 3 shows the complement of original image compared by the output image filtered by our own algorithm.



(i) (ii)

Figure 3. (i) Shows the complement of original image and (ii) the image is filtered by the proposed algorithm.

Know we apply our algorithm of the other very fuzzy mammogram image; the results show as follows,
The Figure 4 shows the very fuzzy original image.

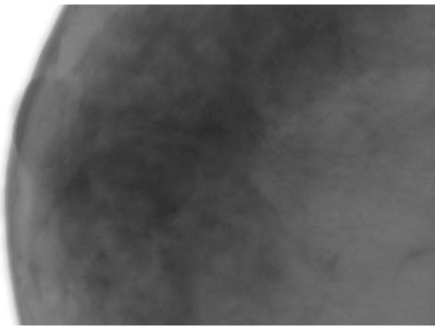


Figure 4. Shows the original image.

As shown in the Figure 2, the Figure 5 shows the region ROI of fuzzy original image.

Figure 5. The extracted ROI.

The Figure 6 shows the eroded image extract by our proposed algorithm.

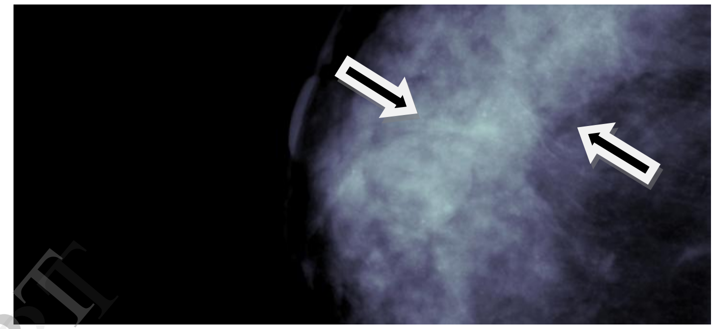


Figure 6. The same fuzzy image filtered by our algorithm.

The Figure 7 shows the zoom of regions extracted in figure 5 on image eroded presented in figure 6.

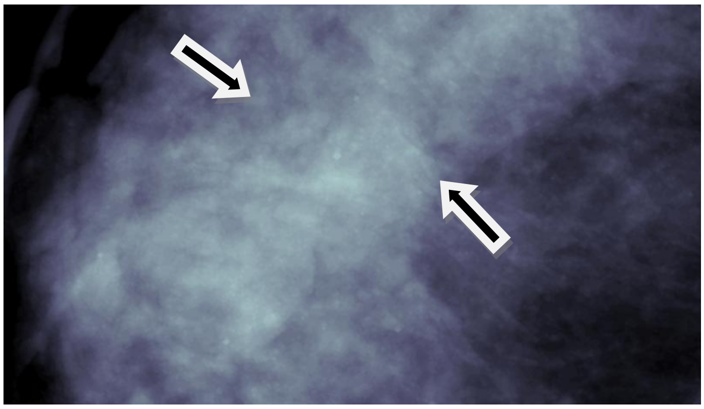


Figure 7. Zooming the regions where have the numerous microcalcifications.

5. Conclusion

We had used the mathematical morphology operator to deduce an algorithm able to detect the microcalcifications in mammograms images, see Figure 3 and Figure 7. We had also seen in Figure 2 how the region of interest, extracted by algorithm 1, helps us to find deepest minima in our original image. Then we focus our study on the same of this region in the filtered image.

The Figure 3 shows the proposed algorithm is able to detect the benign microcalcification in fuzzy image. And the Figure 4 shows the other very fuzzy original image. In this image we can't see any calcification. But when apply the proposed algorithm (see Figure 6) the microcalcifications appear more than before. The result in the Figure 7 shows that our proposed algorithm detects the malignant microcrocalcifications, in spite of having a very fuzzy mammograms image.

We conclude that our algorithm is very powerful to detect well the microcalcifications as benign or malignant.

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